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Predicting Participation in the Las Vegas Water Smart Landscaping (WSL) Program

Abstract:

As arid cities' water scarcity concerns grow, so does the importance of residential water conservation. Understanding the drivers of participation in water conservation programs can aid policymakers in designing programs that achieve conservation and enrollment targets while achieving cost-effectiveness and distributional goals. In this study I identify and analyze the characteristics that drive participation in the Southern Nevada Water Authority's Water Smart Landscaping rebate program – a program that pays homeowners to replace their grass lawns with xeric landscaping – and how those characteristics change over time as rebate values and water prices vary.

In order to determine what characteristics influence participation in this program I gathered data from multiple sources. I use a panel dataset of household water consumption that spans 12 years of approximately 300,000 homes. I merged this dataset with home structural characteristics, geographical, and demographic context. I then use these characteristics in a linear probability model, with school enrollment zone fixed effects to determine their influence on a household's probability of participation. School zones are used to control for unobserved characteristics, such as demographics, which are

not at a household level. I then utilize these school zone fixed effects in a 2nd stage regression to decompose these elements and analyze their effect on participation.

I find that a household's water costs, as reflected in the marginal price faced in the summer and the differential between summer and winter water bills, as well as yard size are primary factors that influence participation. I also show that changes in rebate value and water rates can affect different types of households. There is also evidence to support that neighborhood characteristics affect a household's likelihood of participating.

Predicting Participation in the Las Vegas Water Smart Landscaping (WSL) Program

1. Introduction:

Water scarcity has long been a major concern for cities in arid regions. In the face of limited water resources, these cities have two options to ensure water for their communities. One way is to increase the supply by acquiring water rights. For instance, Nevada has water-banking agreements with both Arizona and the Metropolitan District of Southern California (Harrison, 2009). In these types of agreements one entity sells their unused water to the other, normally with some drought restrictions to protect the seller. However, these types of interstate agreements are rare, as are instate acquisitions of new water sources. This is mainly because the transfer of water from the new source can require extensive funding for conveyance infrastructure on top of the costs of locating the new source and the transaction costs of negotiating an agreement.

A second, often preferred, option is to extend the current supply through water conservation using price and non-price approaches. While there is a long-standing debate as to which of these approaches yields the best outcome, there is still no consensus on which is better at achieving water conservation. Many economists argue the most efficient approach is to use prices to stimulate water conservation; however, raising prices can have undesirable distributional consequences and be politically difficult to achieve. Non-price policies, such as water-use restrictions, water conservation technology adoption, and educational programs, are often the favored choice of water and electric utilities, but may fall short in terms of their conservation goals and economic cost-effectiveness. For instance, rebate programs for durable goods can have so-called “additionality problems” in which many of the people who participate would have replaced the good even in the absence of the rebate (Olmstead & Stavins, 2009; Bennear et al., 2013). Paying households to undertake retrofits that they would have done anyway obviously compromises the cost-effectiveness of such programs. Given these challenges, what should an arid city do to promote water conservation amongst its residents?

This question has confronted water managers in the Las Vegas area for decades. The city almost reached the limits of its water supply in the mid-1990s, which prompted the creation of the Southern Nevada Water Authority (SNWA). The SNWA is now considered by many to be a model for best water management practices. It has created a plethora of programs targeted at water conservation utilizing both price and non-price approaches. Their utilization of the wastewater management system has effectively conserved indoor water use to the point where the majority of the efforts are now focused on outdoor water use. The Water Smart Landscaping (WSL) program is one of the larger and more notable programs that they have created aimed at outdoor water use. It is also the focal point of this study.

The WSL program, informally known as “Cash for Grass,” is a voluntary program that offers a rebate for the replacement of grass lawns for xeric landscaping. The purpose of this study is to identify what observable structural, social and economic factors affected household’s choices to self-select into the program. I then analyze these characteristics to see which are the most influential on participation and affected participation rates. This is done in order to get a better understanding of what types of households are being motivated to enroll and how value changes in water price and the rebate itself altered the uptake rate of the program and the type of household that was incentivized. It also gives the ability to understand the spatial footprint of the uptake of the program across the city and how this uptake correlates with Census-level sociodemographic variables. Understanding these factors illuminates the sorts of users attracted to the WSL rebate program. It also gives insights into how the design of these incentives can be potentially altered to improve program targeting.

To accomplish this I use a variety of data sources that capture aspects of water use and the magnitude of the water bill from household level billing data, structural characteristics of homes (i.e. bedrooms, pool), geographic context (i.e. proximity to parks), and demographic characteristics (i.e. race, income). These characteristics are then used in a linear probability model (LPM) to measure how they affect the probability of a household enrolling in the program. Since demographic information isn't available at a household level I use elementary school enrollment zones "neighborhoods", as a spatial fixed effect. School zones are chosen instead of block group units from the Census, due to the small amount of participants in WSL. By using the geographically larger school zones I minimize the amount of neighborhood units that did not have a participant. It also allows for a finer degree of econometric control over those unobserved features. I then utilize these school zone fixed-effects in a second stage of the model to determine how these elements affect a household's probability of enrollment.

I also analyze the rebate's effect and how this changed over time, rebate dummy variables are utilized in conjunction with time variables. I use a flexible spline function of time along with dummy variables for discrete changes in rebate prices and terms to better understand how the relation between time and rebate value affected participation. These changes of value over time also allow me to examine the differences in participants who chose to enroll at different rebate values. To evaluate these changes, participants are grouped into 4 cohorts based on the rebate value that was active at the time of their enrollment. From there I use summary statistics as well, as well as Kruskal-Wallis tests, to compare cohorts and identified characteristic changes that differentiate one cohort from another.

Understanding the drivers of households' participation in water-saving rebate programs and how variation in the incentives alters both the rate of composition of participants provides the knowledge-base for the creation of better policies. In an arid region, effective water conservation measures are integral to sustainable water practices. It is important to not only understand how efficient a policy is at conserving water, but how that policy can be implemented to achieve higher rates of participation.

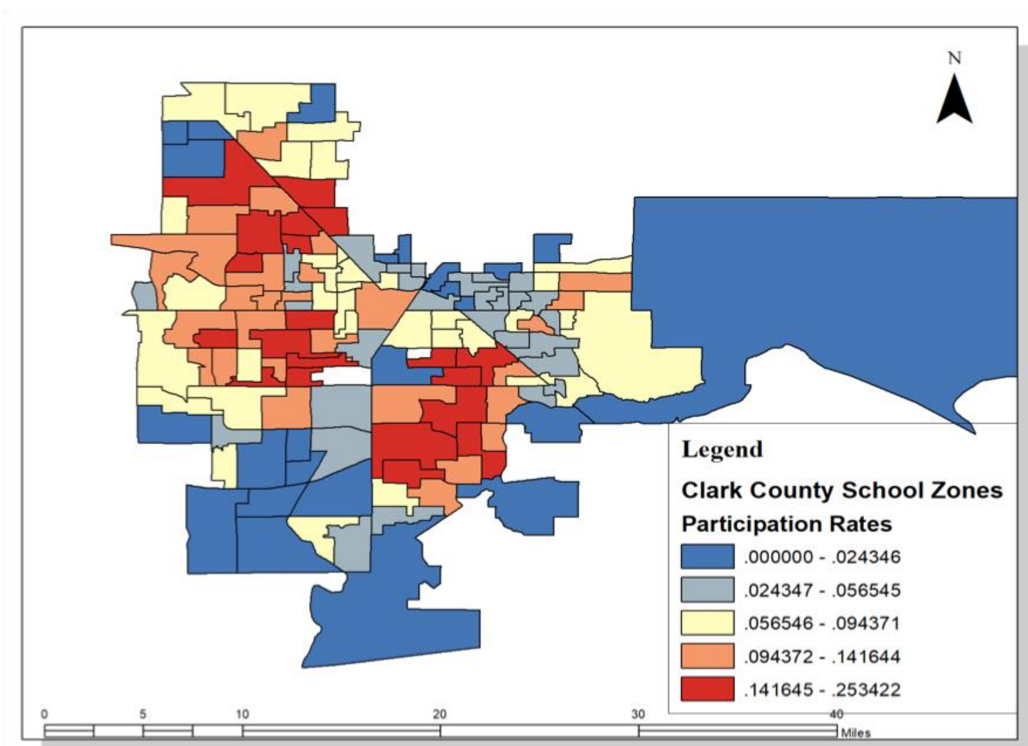

Figure 1 Illustrates the overall percentage of households that participated in the WSL program within each elementary school zone by 2012

2. The Oasis Runs Dry: A Brief History of Water in Las Vegas:

The Las Vegas area has long been seen as an oasis in the desert. Even in the early 1900s its numerous natural springs and close proximity to two rivers provided an attractive location for the railroad to create a train station. The station was the start of Las Vegas and its growing community, but the population boom that was to come was never expected. This lack of foresight is most evident in Nevada's 300,000 acre-feet allotment of water per year in the Colorado River Compact (CRC). At the time of the agreement Nevada had a small population that was easily supported by its instate water resources. It also, at the time, had no way to transport the water from the Colorado River to Las Vegas. This led to Nevada accepting the smallest allotment of any of the Compact states, since the region's leaders never expected the population increase that was to come.

With the addition of the mega-casino in the early 1970s Las Vegas became one of the fastest growing cities in the United States. Nevada small allotment under the CRC became a liability as Las Vegas began closing in on the supply's limit (Harrison, 2009). Water Resources Management Incorporated, an outside consultancy agency, was contracted to assess the water management issues of the area. In 1991, they released their results, which concluded that the area would reach its water supply limits by the mid-1990s. In order to deal with the water shortage five water utility companies and two water waste management companies joined together to form one agency. In 1991 the Southern Nevada Water Authority (SNWA) was established.

The SNWA initiated numerous water conservation programs and practices, none more important than their utilization of the wastewater treatment system. They successfully negotiated with the US Bureau of Reclamation to take advantage of the return flow credit system that *Arizona v California* had set a precedent for previously (Harrison, 2014). The return-flow credits allow treated wastewater to be returned to the Colorado River system and credits the state's allotment with the amount of water returned. Consequently, almost all of Las Vegas' indoor water use that enters the treatment system is reclaimed. This outcome has two major benefits. First, it increases the water supply because any water returned to Lake Mead does not count against Nevada's water allotment from the CRC. Second, since most indoor water is ultimately recycled it incentivized the SNWA to focus their efforts on outdoor water conservation.

SNWA created a mixture of regulatory, educational, and incentive based programs aimed at reducing outdoor water use. For instance, water pricing has been employed using a tiered water price structure with increasing rates to promote lower consumption. Wastewater enforcement has been combined with increased fines to deter poor water management practices. The SNWA hosts numerous events and has created multiple publications all targeted at educating the public on conservation efforts and current drought plans. Rebates are offered for pool covers, smart irrigation clocks, and rain sensors.

SNWA also utilized a block pricing approach for water (see Figure 3). From 1996 -2003 price tiers were set at: first 5 kgal, next 10 kgal, next 25 kgal, and over 40 kgal. Post-2003 the height and placement of tiers changed with the new tiers set with increased pricing at: first 5 kgal ($.98 - $1.16), next 5 kgal ($1.42 - $2.08), next 10 kgal ($1.42 - $3.09), and over 20 kgal ($1.92 - $4.58). This lowered some of the volumetric breakpoints from the previous rate structure and implemented significant increases in price, mainly in the higher tiers. Prices were also raised in Feb. 2007 and once again in May 2008, similarly to the increase in 2003 the largest raises are on the upper tiers.

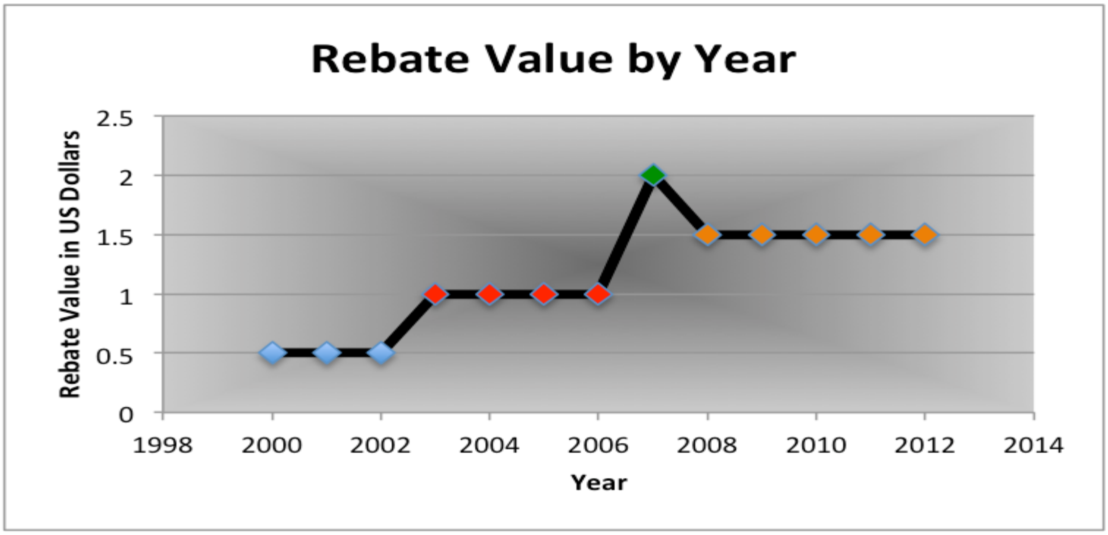

Figure 2 Value of the rebate offered based on year. Blue represents the value and time frame of Cohort 1 or participants who enrolled at the value. Similarly, red represents cohort 2, green represents cohort 3, and cohort 4 is orange.

The WSL program was initiated in 1996 as a pilot program offering a cash rebate for the replacement of grass with xeric landscaping. The program was opened up to all residents in 2000. While the rebates are offered to both commercial and residential landowners, this study will focus only on the residential participants, specifically single-family households. The rebate varied over time between $.50 and $2.00 per square foot. This study evaluates the program over a twelve-year period from 2000 to 2012 (Figure 2 above). During this time period, the only significant change to the program were the length of time the landscape conversion needed to be kept and rebate price per square foot. At the program's inception, there was durability requirement. This changed in 2003, when conversions were required to be held for 5 years and again in 2004 when the term was raised to 10 years or until the property was sold. In 2009 WSL conversions to xeric landscaping were required to be maintained in perpetuity, regardless of the sale of the home.

In order to enroll in the program participants must first file an application. The yard is then assessed to confirm the land is eligible. Once approved a minimum conversion of 50% of lawn must be replaced with either xeric landscaping or permeable artificial turf. A final assessment of the home then occurs to verify the conversion has taken place and meets all requirements before payment can be given. The time it takes to complete this process is approximately 5 months on average (Brelsford & Abbott, 2017a). Currently there is a maximum conversion allowance of 5000 ft^2 per year, with no property receiving a rebate that exceeds $300,000 in a given year.

3. Literature Review/ Research Gap:

A number of studies have examined conservation programs that offer a rebate for a durable good, such as and including the "Cash for Grass" WSL program in Las Vegas (Brelsford & Abbott, 2017a; Sovocol et al., 2006; Bennear et al., 2013; Alcott, 2011). From an economic perspective, much of this research has fallen into two major categories. First, many papers examine the effectiveness of policies in achieving reductions in conservation of a resource (Brelsford & Abbott, 2017a; Alcott, 2011; Datta & Filippini, 2016; Datta & Gulati, 2014; Davis et al., 2014). Others examine the cost-effectiveness of a policy or set of policies in achieving their conservation goals – potentially comparing the relative economic efficiency of alternative approaches (Bennear et al., 2013; Brelsford & Abbott, 2017b). The results of these studies, in many instances, contribute to the debate of the efficiency of price versus non-price approaches. Many studies show that utilizing price to signal scarcity creates a more efficient outcome than non-price approaches (Olmstead, 2010; Grafton & Ward, 2008; Mansur & Olmstead, 2012). However, the cost of the reduction in consumption is often found to be distributed unevenly and is paid mostly by low-income households. This leads to equity issues and is one of the main reasons non-price policies are more common when it comes water demand management. Another issue is raising rates is not politically palatable in many areas. Low water prices are popular, regardless of drought conditions, which make raising prices an uphill political battle (Olmstead & Stavins, 2009).

There is a substantial amount of research demonstrating that voluntary rebate policies are inefficient relative to a direct pricing of water or energy consumption (Bennear et al., 2013; Olmstead, 2010, Timmins, 2003). This is especially true when the subsidies are given in return for replacing durable goods, such as retrofitting old technology with new more efficient technology (Bennear et al., 2013; Davis et al., 2014). The additionality of the rebates in these programs tends to be small. This is due to the overall expected benefit of the rebate being minimized, since many participants would have made the replacement with a smaller rebate and in some cases with no rebate at all (Boomhower & Davis, 2014). There is also the concern of the "rebound effect" occurring after the change has been made eliminating part of the expected benefits (Gillingham et al., 2015). This happens when behavioral changes occur in response to expected gains from using new technology that is more efficient.

Unlike many conservation programs that offer rebates for replacing durable goods, the WSL program doesn't suffer the same deficiencies. While irrigation systems do require replacement at some point, this does not require a complete landscape change and there are no specific time horizons to replace lawns. "Therefore, compared to many other subsidies for the replacement of durable goods, there is little reason to suspect that WSL-rewarded landscape renovations would have occurred in the absence of the subsidy" (Brelsford & Abbott, 2017a). There is also little evidence to suggest any significant "rebound effect" from the program (Brelsford & Abbott, 2017a). These characteristics are uncommon in rebate programs and they contribute to the uniqueness of the WSL program.

The overall size of the WSL program is yet another aspect that adds to its rarity within conservation programs. This study consists of close to 300,000 households over a span of twelve years with monthly observations for water use on each individual residence. This creates a larger sample size over a longer period of time at a higher resolution than most studies on comparable programs. At its inception, WSL program was the first of its kind. Since its creation numerous other incentive based turf removal programs have popped up in other cities located in arid regions across the southwest.

One place that the literature falls short is in studies that identify characteristics that influence participation. Much of the existing literature in this area looks at programs that involve different types of resources that are not directly comparable to water, such as land conservation (Moon, 2013; Sorice et al., 2017; Drescher et al., 2017). There is a scarce amount of research that examines this aspect of water and electricity rebate programs. Understanding which factors affect the likelihood of participation and what type of effect they have is a mostly overlooked facet in the research.

Of the literature that does exist, regardless of resource, a large portion of the papers has their focal point on more subjective characteristics, such as trust and social norms. While these characteristics are important and can help complete the picture of the characteristic components that define a participant, little attention is paid to how household and geographical attributes affect uptake of participation over time when presented with different incentive amounts, which is the focus of this study.

The WSL program affords the opportunity to help fill in these gaps in understanding not only how rebate values can elicit different rates of participation among different type of households, but also its effects on similar households in a characteristically different neighborhood. Due to its strength in additionality and noted lack of a "rebound effect" understanding the differences between households that choose to participate and those who do not can add valuable information into identifying practices that are more effective in influencing higher enrollment. It can also help in identifying what incentives attract specific types of householders, such as homes with high outdoor water use. The results of these examinations can further validate the effects of the WSL program. As more programs are created in the image of the WSL the more important it is to address these aspects.

<u>4. Data</u>:

To identify significant variables and analyze participation in the WSL program, I draw from multiple datasets. I use a SNWA panel dataset of 1999-2012 monthly parcel level residential water consumption spanning 299,872 homes, of which 26,300 are eventual participants in the WSL program. I matched each household's records with the structural characteristics of houses from the Clark County Tax Assessor's records. Due to unrealistic attributes found in the records, such as more bedrooms than rooms in a home, 161 homes are excluded from the study, 22 of which are participants. This left 299,708 households in the study, with 26,278 (8.8%) of them being participants. The dataset was then condensed down from monthly observations over twelve years to one yearly observation, per household[1]. This created a dataset with 3,215,017 observations.

Table 1: 1st Stage Regression Variables Summary Statistics **N = 3,215,017**

	Definitions	Mean	Std. Dev.	Min/Max
Pervious Area	Outdoor porous area, such as grass or soil ($m^2/1000$)	.397	.413	[.001, 132.55]
Impervious Area	Outdoor and indoor non-porous area, such as asphalt, not including the 1st floor area of the home. ($m^2/1000$)	.269	.128	[0, 9.65]
Indoor Area	Total area of the home ($m^2/1000$)	.183	.079	[.025, 3.47]
Pool	Dummy variable for presence of a pool	.245	.43	[0, 1]
Bedrooms	# of bedrooms	3.38	.809	[0, 12]
Bath	# of bathrooms	2.22	.635	[0, 14]
Log Value	Log value of home. Value was calculated by the C. C. Assessor's Office	10.61	.607	[5.3, 16. 43]
Residency	Years elapsed since last sale of home	7.77	7.61	[0, 49]
Resident 2yr	Dummy variable that represents the 1st 2 years after the sale of the home	.19	.389	[0, 1]
Summer Marginal	Highest marginal price a resident is charged per kgal during the summer months (May-Sept.) in a given year.	2.18	.747	[.847, 3.58]
Winter Marginal	Highest marginal price a resident is charged per kgal during the winter months (Oct.-April) in a given year.	2.07	.671	[.855, 3.65]
Seasonal Difference	The difference between the cost of the avg. monthly summer and winter bills in a given year	17.74	32.62	[-513.74, 5744]
Consumption	Avg. monthly water use in kgal for a given year	14.48	14.83	[0, 3009.82]
Park 1/4mi	Dummy variable that identifies if there is a park with a water feature within a 1/4 mile of the home	.063	.243	[0, 1]
Rebate 2003	Dummy variable that identifies years rebate value was $1	.305	.461	[0, 1]
Rebate 2007	Dummy variable for the rebate value $2.00	.084	.278	[0, 1]
Rebate 2008	Dummy variable for the rebate value $1.50	.424	.494	[0, 1]
Vintage 1960	Dummy variable which represents homes built before 1960	.045	.208	[0, 1]
Vintage 1984	Dummy variable for homes built between 1961-1984	.24	.43	[0, 1]
Vintage 1992	Dummy variable for homes built between 1985-1992	.135	.341	[0, 1]
Vintage 1997	Dummy variable for homes built between 1993-1997	.174	(.379)	[0, 1]

[1]Billing records are related to the home and not household. This is due in part to a lack of data on the transfer of homes, which would allow for the identification of tenet changes in rental properties. In this paper the terms "home" and "household" will be used synonymously even though there is a lack of equivalence.

Vintage 2002	Dummy variable for homes built between 1998-2002	.356	(.479)	[0, 1]
Vintage 2012	Dummy variable for homes built after 2002	.19	(.392)	[0, 1]
Year	Elapsed time in years of the study 2000-2012, with 2000 = 1	7.415	(3.64)	[1, 13]

This data was then merged with spatial data including nearby parks and water bodies. This was done under the assumption that public green space and/or bodies of water could act as a substitutes or complements to the services provided by a home's private lawn. The mapping data for parks was collected from the Clark County Government Center. Park water features data came from multiple local government websites.[2] Elementary school enrollment zones data came from the Clark County School District. School zones are chosen as a proxy for "neighborhoods", since these zones have been found to share similar demographic characteristics (Clark, 1987; Richards, 2014). The spatial characteristics are then linked to a household's parcel using ArcView GIS software. Variables are created for park distance from a household, parks with a water feature (i.e. Pool, pond, etc.) distance from household, and the number of parks with and without water features that fell within specific distances from a residence. Distance is defined as the Euclidian distance from the residence to the park and does not necessarily represent a true walking distance. Households are also matched with their elementary school enrollment zone.

[2] Websites used: www.clarkcountynv.gov, www.lasvegasnevada.gov, www.summerlink.com, www.cityofnorthlasvegas.com, www.cityofhenderson.com

Table 2: 2nd Stage Regression Variables **N = 135**

	Definition	Mean	Std. Dev.	Min/Max
Poverty Income	% of people with an income < $25,000	.226	(.13)	[.064, .645]
Low Income	% of people with an income between $25,001-$35,000	.123	(.037)	[.045, .208]
Low Mid Income	% of people with an income between $35,001-$45,000	.28	(.048)	[.14, .422]
Middle Income	% of people with an income between $45,001-$100,000	.241	(.086)	[.054, .428]
High Mid Income	% of people with an income between $100,001-$150,000	.084	(.051)	[.003, .234]
High Income	% of people with an income < $150,000	.047	(.041)	[.002, .27]
HH Size 1&2	% of households whose size is 2 or less people	.567	(.094)	[.282, .778]
HH Size 3&4	% of households whose size is 3 or 4 people	.303	(.056)	[.14, .433]
HH Size 5&up	% of households whose size is 5 or more people	.13	(.056)	[.048, .351]
No HS Diploma	% of people who have a 12th grade education or less, without a high school diploma or equivalent	.204	(.121)	[.047, .639]
HS Diploma	% of people who have a H.S. diploma or its equivalent.	.301	(.049)	[.164, .417]
Some College	% of people who have some college or an associates degree	.32	(.067)	[.118, .444]
Bachelor Degree	% of people with an Bachelors Degree	.116	(.057)	[.018, .268]
Graduate Degree	% of people with a Graduate or Professional Degree	.058	(.035)	[.004, .159]
White	% of people who identify their race as White & non-Hispanic	.761	(.16)	[.091, .961]
Black	% of people who identify their race as Black or African American	.099	(.144)	[0, .834]
Asian	% of people who identify their race as Asian	.046	(.03)	[0, .174]
Other Race	% of people who identify their race as some other race or combination of races.	.093	(.056)	[0, .336]
Hispanic	% of people who identify as Hispanic regardless of race.	.148	(.106)	[.026, .571]
Owner	% of households who own their home	.654	(.21)	[.07, .964]
Renter	% of households who rent their home	.346	(.21)	[.036, .93]
Under 18	% of people who are < 18	.255	(.049)	[.152, .405]
Age 18to29	% of people who are between the ages of 18 to 29	.163	(.042)	[.047, .291]
Age 30to44	% of people who are between the ages of 30 to 44	.317	(.033)	[.206, .422]
Age 45to64	% of people who are between the ages of 35 to 54	.163	(.037)	[.078, .263]

Over 65	% of people who are over 65	.102	(.044)	[.037, .377]

**All % rates are in relation to elementary school enrollment zones.*

The final datasets I utilize are demographic characteristics from the U.S Census Bureau. I utilized the 2000 Census surveys for block level data on income, education, race, age, home ownership, and household size. Income was composed into six groups for simplicity: poverty level (>$25,000), low income ($25,000-$35,000), low middle income ($35,000-$45,000), middle income ($45,000-$100,000), high middle income ($100,000-$150,000), and high income (over $150,000). Household size was also grouped: 1-2 people, 3-4 people, and more than 5 people. Educational data consists of: no High School (HS) diploma or Equivalent, HS diploma or equivalent, some college or Associates Degree, Bachelor degree, graduate or professional degree. Age was separated into: under 18, 18 to 29, 30 to 44, 45 to 64, and over 65. Race & ethnicity was broken down into Non-Hispanic White, Black, or Asian, Hispanic of any race, and other. Ownership has two categories to identify residents who own their home and those who rent. Utilizing this block level data, weighted averages for these characteristics are created for the school zones. The averages are based on block demographics within the enrollment zones. Each household was then matched with their corresponding school zone and the demographic attributes.

5. Estimation Models & Methodology:

The nature of this study brings about some methodological concerns that needed to be addressed. The first concern is dealing with the binary outcome variable. A linear probability model (LPM) was used for models 1 - 4 (Cameron & Trivedi, 2010). While logit or probit models were also considered, there are several reasons that made the LPM the more appropriate choice. First, our overriding concern is to provide easily interpretable estimates of the average marginal effects of changes in the exogenous variables of the model on changes in the probability of WSL participation. The LPM has robust properties in this regard, despite the potential for it to predict outside of the (0,1) interval for individual probabilities in the presence of continuous covariates. Second, due to the large size of the dataset using a logit model with a large number of spatial fixed effects led to convergence challenges on a laptop computer. Third, and most importantly, the LPM leads to a natural interpretation for the elementary school zones spatial fixed effects included in the models. Since I use the estimated values of these fixed effects as dependent variables in a second stage regression, it was important to have them in easily interpretable units. The fixed effects in a LPM are in units of probability; however this is not the case for the logit or probit model. Cluster-robust standard errors are used for all models. Clusters are defined at a school zone level in order to control for heteroskedasticity, as well as, spatial and serial correlation in the unobserved characteristics that influence participation.

Numerous structural characteristics of the home are utilized in the 1st stage of the model, which give a detailed picture of the physical house and the composition of its lot. However, the only observable household characteristics in this stage pertain to water consumption and length of residency within the home. In order to control for unobservable heterogeneity in these neighborhood demographics, I use elementary school enrollment zones as a spatial fixed effect. These dummy variables serve to absorb the average values of sociodemographic attributes and other unobserved spatially distributed correlates of WSL participation. I then take these school enrollment zone effects into the

2nd stage, where they are regressed on the aforementioned Census demographic variables to understand what factors influence these effects.

I consider several models of increasing complexity. In the first model the probability of participation incorporates the observable structural characteristics of a specific home, within a specific spatial zone, over a period of time. The model takes the form:

$$P_{it} = X'_{it}\beta + D'_{it}\delta + \mathrm{T}'_{i}\gamma + \varepsilon_{it} \qquad (1)$$

Where P represents the probability of participation of i, an individual household, at a specific period of time *t*. X' is a vector of house structure and length of residency variables for a home, D' is a vector of year-specific dummy variables. There are 2 main sets of dummy variables. One set indicates the rebate value that was active at a given time. The other set are vintage bins that are based on regulations faced by new construction over different time periods as well as past findings about the efficiency of a home's water infrastructure (Brelsford & Abbott, 2017b). Homes are grouped into these bins based on their build year.

T' is a vector of time trend variables. In Model 1 the T are variables years elapsed and years elapsed squared. The second model adds to the first by modifying the time trend variables. In Model 2, I utilize linear splines with three knots placed over the twelve-year period of the study, at years 2003, 2007, and 2009. These years are chosen because they coincide with changes in both the rebate value (see Figure 2) and water rates. These spline variables replace the time variables in Model 1.

In Model 3, a neighborhood fixed-effect is added to Model 2, which is associated with elementary school enrollment zones and takes this form:

$$P_{it} = X'_{it}\beta + D'_{it}\delta + \mathrm{T}'_{i}\gamma + \alpha_s + \varepsilon_{it} \qquad (2)$$

Here α_s represents the spatial fixed effects of elementary school enrollment zone *s*. This was done under the assumption that there are unobservable spatial relationships amongst households located within these school zones and as such, error terms within these zones are likely to be correlated with observed covariates due to these shared characteristics. Given that I do not observe household-level sociodemographic data, I utilize these fixed effects to absorb the average effects of demographic variability across neighborhoods.

The final model in the first stage, Model 4, is similar to Model 3. It is also a fixed-effect LPM except in this model I add household-level economic variables from the monthly billing data. The model's form is:

$$P_{it} = X'_{it}\beta + D'_{it}\delta + \mathrm{T}'_{i}\gamma + C'_{it}\theta + \alpha_s + \varepsilon_{it} \quad (3)$$

C represents a vector of economic variables for a household that has a one-year lag. I utilize a lag to avoid issues of simultaneity (joint causation) between water consumption levels and WSL participation decisions. The lag also accounts for the fact that households, when contemplating long-run investments, like landscape remodeling, are likely to draw upon recent historic data to project future benefits and costs of the investment. Finally, the lag accommodates the time it takes from the initial application to the program to fulfilling the requirements to qualify for the rebate.

In the second stage I begin the analysis of the school zone fixed effects from the most complete first-stage model (Model 4). The second stage model's form is:

$$\hat{\alpha}_s = \psi_s + Zone_s{}'\lambda + \nu_s \qquad (4)$$

Here ψ_s.is the intercept. $Zone_s$ is a vector of demographic variables that was calculated from weighted U.S. census data. The second stage is estimated using heteroskedasticity-robust standard errors.

Spatial fixed effects are defined at the school attendance zone, whereas U.S. Census data are available at the block-group. In general, each school zone contains multiple block-groups. I weight the block-groups in each attendance zone to acquire more representative estimates of the presence of a demographic characteristic within a school zone. This is calculated by estimating the number of people or households with a demographic characteristic per acre of the Census block-group. Using these estimates in conjunction with the amount of acres of each block-group that falls within a specific school zone I calculate the expected the number of people/households with the characteristic in the zone. I then use the results with the total population of the zone to determine the weighted average.

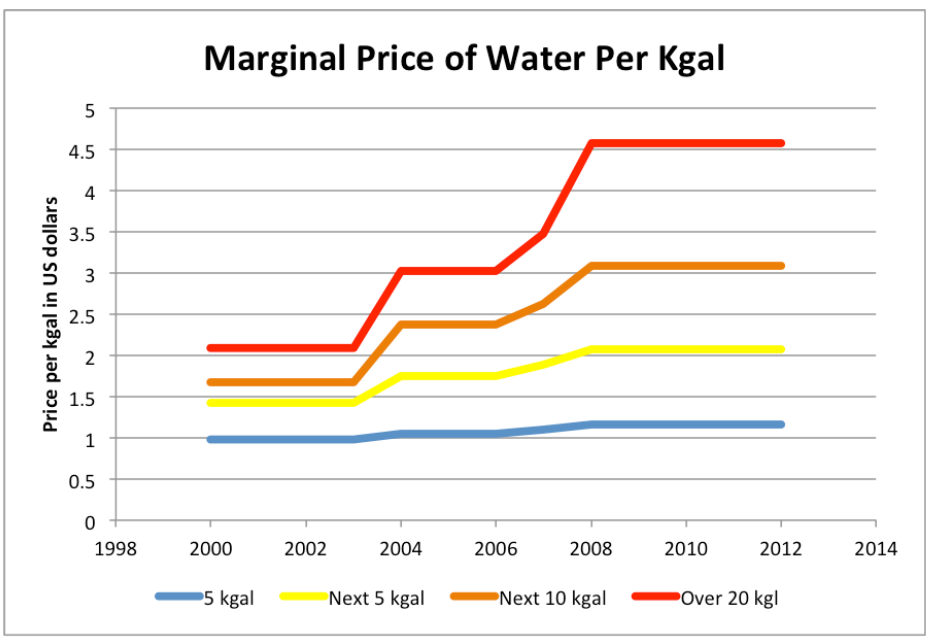

Figure 3 Shows the block level marginal price of water and the changes of price between 2000-2012. Prices before 2003 were set to different tier levels, thus prices during this time are estimated based on pre 2003 prices to fit post 2003 tier levels.

6.1 Results and Interpretations – Cohort Analysis

In order to get a better understanding of how changes and rebate value and water rates influenced who participated in the program, participants are split up into 4 groups. Each group identifies the value of the rebate at the time of enrollment of the participant. Thus cohort 1 holds all participants who enrolled at a rebate value of $.50, cohort 2 are those who signed up at $1, cohort 3 at $2, and finally cohort at $150.

In an examination of the WSL cohorts I first look at pervious area, which for simplicity I will refer to as "yard size." A Kruskal-Wallis test shows that there is a statistically significant difference in the yard size by different cohorts (χ^2=111.014, $p < .01$). Figure 4 shows a small decrease in the mean yard size from cohort 1 – 3, but then a slight rebound in cohort 4. Thus as the rebate increased household yards became smaller on average. When the rebate dropped from $2 per sq. ft. to $1.50 in cohort group 4, yard size increased, albeit only slightly. There is a similar trend found in consumption, seen in also in Figure 4, which was also found to be significant (χ^2= 489.53, $p < .01$). Since yard size is assumed to correlate with water-use, these similarities are not surprising. The size of the yard, assuming the yard contains grass, will determine the amount of water needed to maintain it. However, it is important to recognize that my analysis does not take into account the effects of the depletion of potential applicants from the sample pool over time. Further analysis is required to understand what role if any this played in altering the composition of the different cohorts.

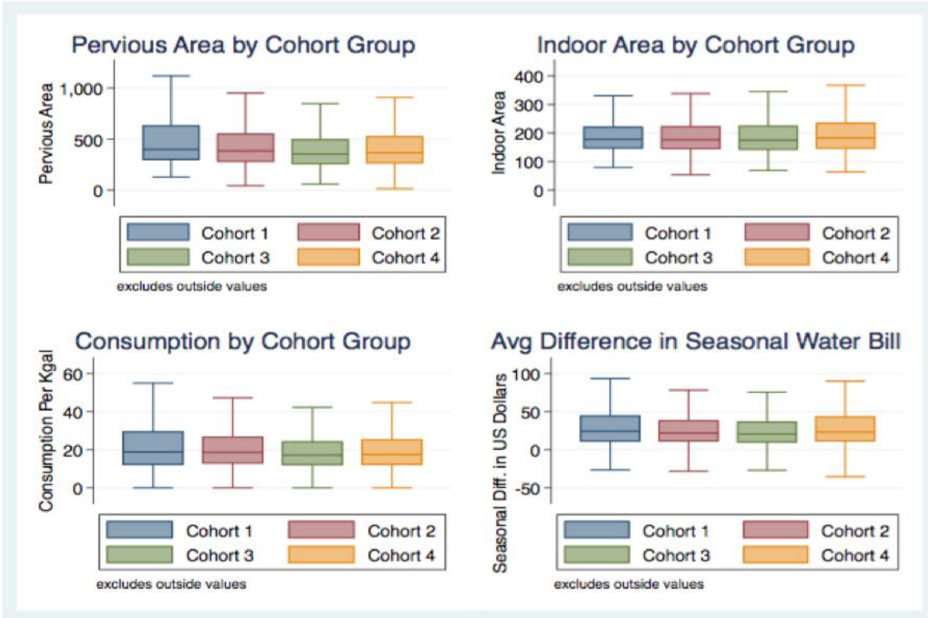

Figure 4 (Top-left) Shows pervious area cohorts. (Top-right) Shows indoor area of each cohort. (Bottom-right) Shows difference in avg. seasonal water bill of cohorts. (Bottom-left) Shows the average monthly consumption of cohorts.

Average seasonal difference is used as a proxy for the cost of outdoor water use of a home. Similar to yard size there is a statistically significant difference in outdoor water cost between cohorts (χ^2= 412.748, p < .01). Figure 4 shows groups 1 and 4 had similar average cost associated with outdoor water use, as did cohort 2 and 3. However, referring back to the average consumption, cohort 4 consumes less on average compared to cohort 1. This shows that while cohort 4 uses less water on average, their cost of outdoor water use is virtually the same as cohort 1. This similarity in cost is most likely due to the increase in price of water, specifically on high water use. As seen in Figure 3, each cohort faced an increasing marginal price on water, with the largest increases occurring on water use over 20 kgal. These increases that target high water consumption happen first in 2003, then again in 2007 and 2008.

Interestingly, the amount of lawn converted does not follow the same trend as yard size. Figure 5 shows that in cohort 2 the mean amount converted is higher than cohort 1. So while cohort 1 had larger yards on average, cohort 2 converted more of their yard. This may be due to the rebate increase making larger conversions more cost efficient; especially since the water prices saw a significant increase in 2003. Cohorts 3 sees a dip in conversion area, where as cohort 4 has a slight increase.

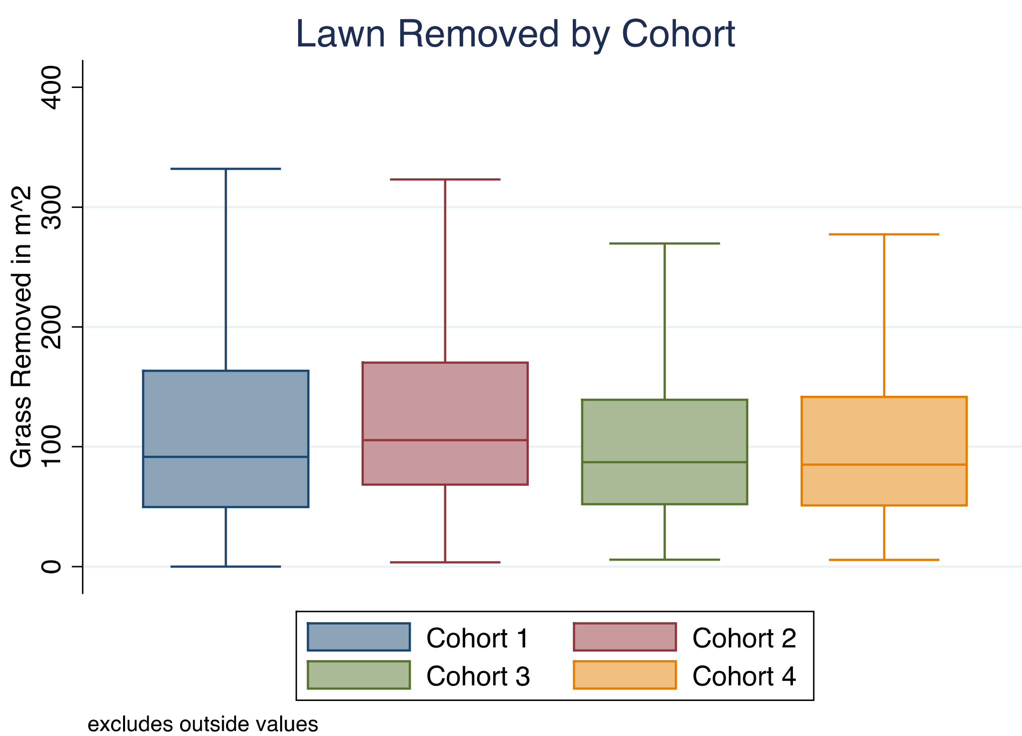

Figure 5 **Illustrates the average amount of grass converted of a household in each cohort**

Table 3: 1st Stage Summary Statistics

	Participants	Non-Participants	All Households
Consumption (kgal)	21.64	14.02	14.48
	(15.61)	(14.66)	(14.83)
	[0, 330.74]	[0, 3009.82]	[0, 3009.82]
Summer Marginal	2.32	2.17	2.18
(US Dollars)	(.53)	(.76)	(.75)
	[.85, 3.58]	[.85, 3.58]	[.85, 3.58]
Winter Marginal	2.12	2.04	2.05
(US Dollars)	(.52)	(.68)	(.67)
	[.86, 3.65]	[.85, 3.65]	[.85, 3.65]
Seasonal Difference	32.88	16.79	17.74
(US Dollars)	(37.79)	(32.26)	(32.62)
	[187.51, 875.73]	[-513.74, 5744]	[-513.74, 5744]
Pervious Area (m^2/1000)	.52	.39	.4
	(.47)	(.41)	(.408)
	[.013, 17.27]	[.0008, 132.55]	[.0008, 132.55]
Impervious Area (m^2/1000)	.32	.26	.27
	(.14)	(.13)	(.13)
	[0, 2.14]	[0, 9.65]	[0, 9.65]
Indoor Area (m^2/1000)	.197	.19	.18
	(.077)	(.083)	(.079)
	[.054, 1.23]	[.025, 3.47]	[.025, 3.47]
Bedrooms	3.46	3.38	3.38
	(.804)	(.81)	(.81)
	[0, 9]	[0, 12]	[0, 12]
Bath	2.28	2.24	2.22
	(.62)	(.66)	(.64)
	[0, 7.5]	[0, 14]	[0, 14]
Build Year	1988.62	1992.35	1989.91
	(12.19)	(14.85)	(14.64)
	[1925, 2011]	[1912, 2012]	[1912, 2012]
Log value	10.76	10.66	10.61
	(.54)	(.62)	(.61)
	[8.93, 14.18]	[5.298, 16.43]	[5.298, 16.43]
Park 1/4mi	.06	.056	.06
	(.24)	(.23)	(.24)
	[0, 1]	[0, 1]	[0,1]

* The figures in the rows for each variable are in this order: mean, (std. dev.), and [min, max]. All participant statistics are based on pre-WSL observations.

6.2 Results and Interpretations of 1st Stage: House Structure

When looking at what differentiates homes of participants from non-participants, it is important to note that all observations for participants after enrollment are omitted from the data set. This brings the total number of observations down to 2,158,762 and allows for all results to be based on pre-treatment observations. One difference that can be gleaned from Table 3 is pervious area. This distinct difference in pervious area size between participants and non-participants can also be visualized in Figure 6. However, the amount of indoor area is relatively the same on average. Participants only have slightly larger homes on average, which can be seen in Figure 6.

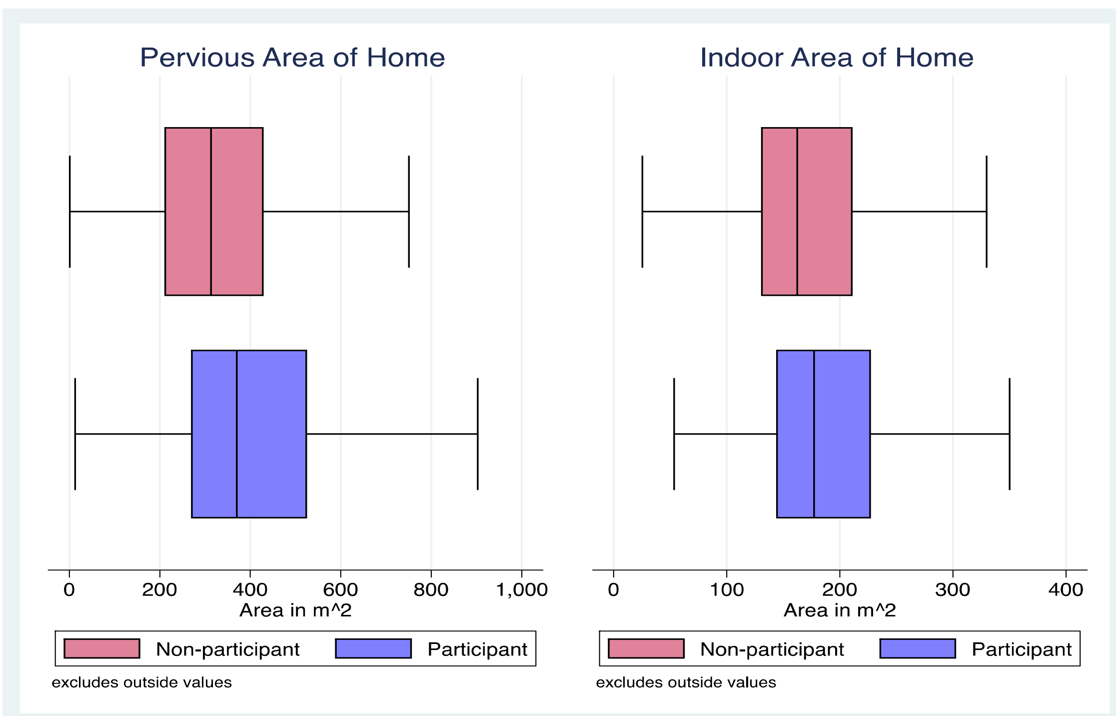

Figure 6 (Left) Comparison of pervious area between participants and non-participants. (Right) Comparison of indoor space between the two groups.

The estimates for the four first-stage models are presented in Table 3. Almost all the variables are significant across all 4 models at a 1 percent level, with the exceptions of Pervious Area, Bedrooms, Pool, Park 1/4mi, and Vintage 1984. Out of those 5 exceptions, only Vintage 1984 is insignificant across all models.

Pervious Area is significant at a 1 percent level in the first 3 models, but loses some significance in Model 4. Its marginal effect also drops slightly in Model 3 due to the addition of fixed-effects, but then decreases in Model 4 to approximately one-third the effect of the other models. This is not surprising as Model 4 includes economic variables that are capturing water use (particularly the seasonal difference variable), which is correlated with the size of pervious area (ρ= .4). This allows for the conclusion that while Pervious Area is not highly significant in the final model, it still is economically relevant. Indoor Area had a relatively large negative effect on participation. An increase of 1 standard deviation in indoor area, holding constant pervious and impervious outdoor area, has a -0.004 effect on the probability of participation. By comparison, an increase of 1 standard deviation in pervious outdoor area has less than a 0.0004 effect on participation. While these effects may initially appear small, it is important to remember that the overall annual probability of participation for a household is 0.0065.

Vintage bins, aside from Vintage 1984, have a notable effect on participation, both positively and negatively. Using homes built before 1960 as the base of the model, it shows that those constructed between 1985 and 1992 are found to have an increase of approximately 0.003 on the probability of participation. Those built between 1993 through 1997 had a slightly less positive effect of 0.0025. Homes built after 1997 have a negative effect on participation, with homes built between 1998 and 2002 having a -0.0026 effect of participation and those built after 2002 having the largest negative effect at -0.0079. This suggests that newer homes are less likely to participate; this is likely driven by smaller shares of green landscaping, on smaller lots (Brelsford and Abbott 2017b) in newer developments. This large negative effect found in Vintage 2012 makes sense since this represents homes built after 2003. In 2003 a law was passed that didn't allow any turf in front yards of new construction. More efficient plumbing technology may have also reduced participation by reducing the household's indoor water consumption. For perspective, there is a 0.011 difference in probability between a home that falls into the Vintage 1992 bin and one that is built after 2003 in Vintage 2012.

Table 3: 1st Stage Estimation Results

	Model 1	**Model 2**	**Model 3**	**Model 4**
Pervious Area	0.00345***	0.00344***	0.00302***	0.00107*
	(0.000657)	(0.000657)	(0.000629)	(0.000569)
Impervious Area	0.0134***	0.0134***	0.0102***	0.00600***
	(0.00223)	(0.00223)	(0.00137)	(0.00118)
Indoor Area	-0.0303***	-0.0303***	-0.0224***	-0.0299***
	(0.00326)	(0.00325)	(0.00323)	(0.00375)
Pool	0.000199	0.000193	-0.00000961	-0.00119***
	(0.000358)	(0.000358)	(0.000339)	(0.000350)
Bedrooms	0.00122***	0.00122***	0.000681**	0.000566**
	(0.000384)	(0.000384)	(0.000280)	(0.000257)
Bath	-0.00142***	-0.00142***	-0.00109***	-0.00120***
	(0.000317)	(0.000317)	(0.000249)	(0.000248)
Log Value	0.00649***	0.00651***	0.00556***	0.00401***
	(0.000629)	(0.000629)	(0.00104)	(0.000970)
Residency	0.000123***	0.000125***	0.000131***	0.0000993***
	(0.0000188)	(0.0000188)	(0.0000175)	(0.0000172)
Resident < 2yr	0.00193***	0.00205***	0.00206***	0.00250***
	(0.000283)	(0.000283)	(0.000284)	(0.000288)
Park 1/4mi	-0.000718	-0.000718	-0.000664	-0.000850*
	(0.000601)	(0.000601)	(0.000561)	(0.000479)
Rebate 2003 (Dummy for	0.0125***	0.0129***	0.0129***	0.0108***
rebate for 2003- 2006)	(0.00131)	(0.00111)	(0.00112)	(0.00104)
Rebate 2007 (Dummy for	0.0164***	0.0150***	0.0150***	0.0147***
rebate for 2007)	(0.00138)	(0.00141)	(0.00141)	(0.00140)
Rebate 2008 (Dummy for	0.0185***	0.0254***	0.0254***	0.0264***
rebate for 2008- 2012)	(0.00158)	(0.00192)	(0.00191)	(0.00196)
Vintage 1984	0.000537	0.000533	0.000719	0.000746
	(0.000614)	(0.000613)	(0.000794)	(0.000733)
Vintage 1992	0.00441***	0.00440***	0.00289***	0.00296***

	(0.00109)	(0.00109)	(0.000977)	(0.000919)
Vintage 1997	0.00327***	0.00326***	0.00259***	0.00252***
	(0.000994)	(0.000997)	(0.000688)	(0.000648)
Vintage 2002	-0.00210***	-0.00210***	-0.00326***	-0.00261***
	(0.000534)	(0.000535)	(0.000677)	(0.000612)
Vintage 2012	-0.00872***	-0.00875***	-0.0107***	-0.00794***
	(0.000631)	(0.000630)	(0.000901)	(0.000727)
Year	0.00172***			
	(0.000272)			
Year^2	-0.000195***			
	(0.0000150)			
Year: (.,4)		0.000255***	0.000247**	0.00176***
		(0.0000967)	(0.0000986)	(0.000211)
Year: (4,8)		-0.000110	-0.0000850	-0.000928***
		(0.000258)	(0.000248)	(0.000292)
Year: (8,10)		-0.00703***	-0.00701***	-0.00901***
		(0.000501)	(0.000499)	(0.000626)
Year: (10,.)		-0.00168***	-0.00168***	-0.00131***
		(0.000126)	(0.000125)	(0.000110)
Summer Marginal				0.00364***
				(0.000303)
Winter Marginal				0.000909***
				(0.000208)
Seasonal Difference				0.000113***
				(0.00000985)
Consumption				-0.0000973***
				(0.0000145)
Constant	-0.0731***	-0.0713***	-0.0595***	-0.0516***
	(0.00592)	(0.00585)	(0.0100)	(0.00942)
Fixed-Effects			X	X
Observations	2,158,762	2,158,762	2,158,762	2,148,518
R^2	0.006	0.006	0.006	0.008

6.3 Results and Interpretations 1st Stage: Time Trends and Rebates

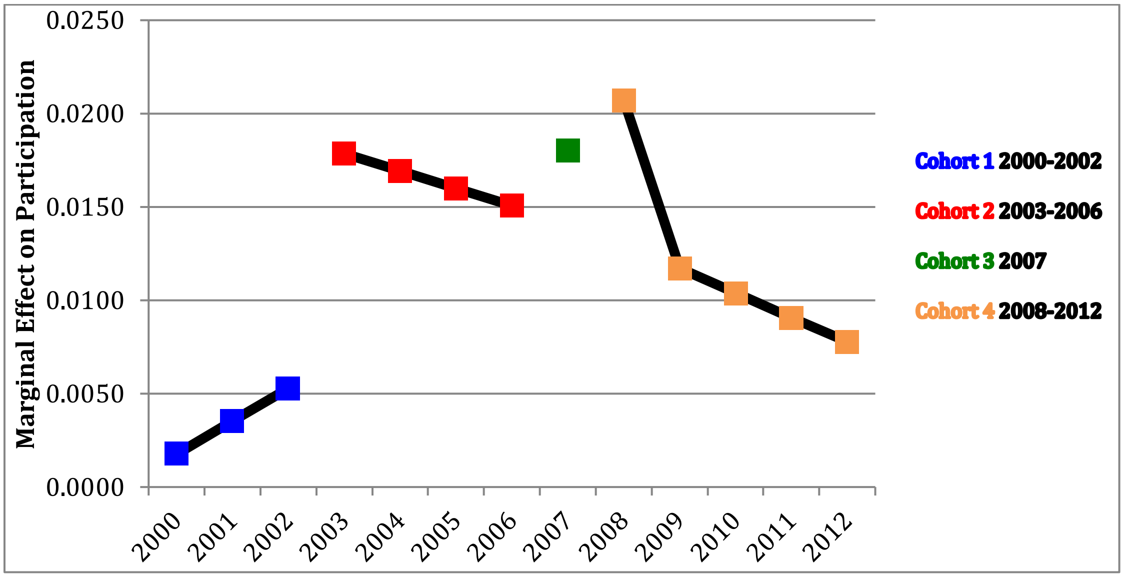

Figure 7 Shows the combined influence of the summation of the time splines and rebate dummies on the probability of participation over time.

Figure 7 adds the predicted values from the spline regression in Model 4 on top of the contemporaneous dummy variable for the rebate cohort. This specification allows both smooth trends in WSL participation within each cohort and discontinuous jumps between cohorts. From 2000 to 2002 there is a steady increase on the probability of participation. In 2003 there is a steep jump in likelihood of participation that coincides with the new rebate of $1. After this bump, the time trend in participation slows until 2007, when WSL rebates increase to $2. Here there is another increase in participation similar to 2003. In 2008 the rebate decreases to $1.50, but even though the value drops there is another increase in the probability of participation. After the 2008 rebate there is a decrease in probability each year until 2012. This may imply that participation is likely to occur in the presence of a new rebate value that is not necessarily tied to the rebate increasing. This could be due to the shock of the value change on households. Households who may have been contemplating participation are motivated by the price change. However, as the price change gets further removed they are less likely to act. During this time period there were other events, such as the 2008 financial crisis, that may have also influenced participation. Since I am unable to separate the effects of these events from those of the water policy changes, I cannot make any strong conclusions as to the overall effect of the rebate change on participation.

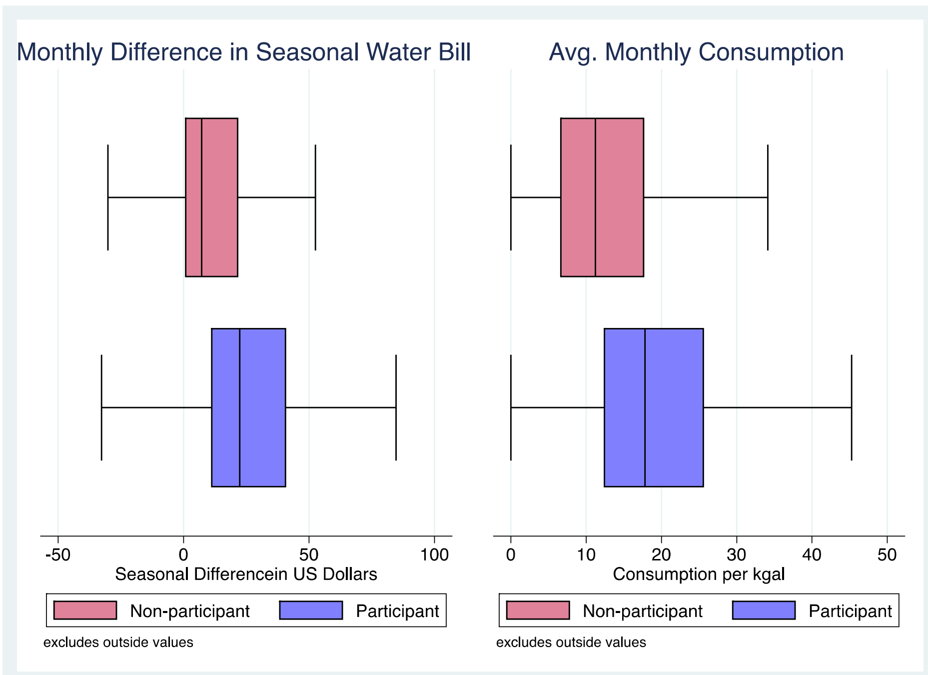

Figure 8 (Left) Displays the difference in the avg. monthly water bill in the summer from the winter. (Right) Shows the difference in avg. monthly consumption between the 2 groups.

6.4 Results and Interpretations 1st Stage: Water Consumption

Water consumption and economic variables play a significant role in explaining participation rates. When looking at consumption, Table 3 shows that participants used 7 kgal more per month on average before enrollment than non-participants. This is visualized by the right hand-side graph in Figure 8 where the 50-percentile line for participants almost perfectly aligned with the 75-percentile line for non-participants.

Another characteristic that stands out is Seasonal Difference, or the cost of outdoor water use. Table 2 shows that the mean Seasonal Difference for participants (mean = 32.88) is approximately twice that of non-participants (mean = 16.79). This is also reflected in the left hand side graph in Figure 8. In other words, households that chose to participate paid double the amount per month on average for outdoor water use than non-participants.

In Model 4 the effects of water usage and economic variables have been added to the regression. While the highest price of water per kilo-gallon paid has a positive effect on enrollment for both winter and summer, the summer price has a notably greater effect at 0.0036 for every additional dollar added to the marginal price per kgal. The difference in the average seasonal bill between summer and winter, a proxy for outdoor water costs, has a positive effect on participation. An increase of 1 standard deviation in seasonal difference has 0.0037 effect. These results suggest that the cost of outdoor water use is primary factor in influencing households to participate.

Household consumption has a negative effect on participation. Since the seasonal difference is controlling for outdoor water use and marginal pricing, consumption is essentially representing indoor water use holding the price of water constant. An increase of 1 standard deviation of consumption decreases the likelihood of participating by approximately 0.001. This makes sense as the main benefits of conversion for a household is in the savings received from the reduction in outdoor water use. Thus households with high indoor water use would not have the same incentive to participate.

In terms of the main driving forces behind participation, it would be fair to say that water use and its associated costs would be high on the list. Both the price of water, especially in the summer, and the costs of outdoor water use have positive effects of participation. These costs can be connected to yard size, which as previously discussed in Sec. 6.2 are larger for participants. This suggests that the program is strongly selecting toward homes with high outdoor water use.

6.5 Results and Interpretations 1st Stage: Residency &Parks

Length of ownership of a home, which is represented by Residency, is found to be significant and positive. The effect on participation is relatively small, as a decade of residency has an effect of less than 0.001. Resident <2yr, which captures the probability of participation within the first two years of purchasing a home, is also positive and has relatively large effect on the probability of participation. A new homeowner in their second year of residency has an increased probability of participation of 0.0026. In a comparison of the 2 variables, I find that while every year of residency in a home does increase the likelihood of joining the WSL program, a new homeowner has a higher probability of enrollment in the first two years than a resident of 25 years.

These somewhat surprising results of the effects of residency, is similar to those found in a study done in Phoenix, AZ (Larson et al., 2017). Larson et al. found that long-term residents prefer grass lawns in comparison to residents that were newer to the area. The results here somewhat mirror those results, as I find that new homeowners in the Vegas area have a notably higher probability of participation and foregoing their grass than long term residents do. I originally assumed that long-term residents would have a greater knowledge of local water issues in comparison to new homeowners and therefore expected a weaker effect from new ownership.

An alternative hypothesis is this is due to a “remodeling” effect that is associated with new home ownership. New homeowners are likely to remodel their homes to suit their needs. In this process homeowners might have a higher willingness to opt for conversion as part of the remodel. Conversions during remodeling may also be preferable to new owners whose intentions are to rent or “flip” the home to turn a profit, as xeric landscaping requires less maintenance. While I have discussed the possibilities of a “remodeling” effect and a preference of long-term residents for grass lawns as separate, I would argue that it is some combination of these factors that drives this “new resident” effect on participation.

It’s worth noting that in this study I use time elapsed since the date of last sale of a home to establish a proxy for residency in the area. It does not take into account whether the homeowner was moving from within the area or from outside of the area. Thus, further research should examine the dynamics between various residency attributes, landscape choices, and implications for water demand.

The first stage of the model yields another interesting result, for the outcome of Parks ¼ mi. My initial hypothesis was that parks would act as a substitute for lawns, and therefore, households that are within walking distance to parks would be more likely to participate in the program. However, the presence of a park is found to be insignificant in earlier iterations of the current models. What is found to be significant, though only at a 10 percent level, is the presence of a park that has a water feature, such as a pool or lake, within a ¼ mi. of a home. However, these parks had a negative effect on participation implying that people who chose to live near these types of parks do so because they value their green spaces, lawns included.

6.6 Results and Interpretations 2nd Stage: Demographics

Table 4: 2nd Stage Estimation Results

	Model 1
Low Income	-0.00548
	(0.0124)
Low Mid Income	0.0126
	(0.0103)
Middle Income	0.0207
	(0.0137)
High Mid Income	0.0300**
	(0.0128)
High Income	-0.00944
	(0.0103)
HH Size 3&4	0.0157
	(0.0145)
HH Size 5&up	-0.0390**
	(0.0183)
HS Diploma	0.00417
	(0.0136)
Some College	0.0110
	(0.0113)
Bachelor Degree	0.0154
	(0.0231)
Graduate Degree	-0.0420*
	(0.0253)
White	-0.0195
	(0.0165)
Black	-0.0108
	(0.0145)
Asian	-0.0531**
	(0.0249)
Hispanic	0.0144
	(0.0132)
Own Home	-0.00756
	(0.00464)
Age 18to29	-0.0232
	(0.0303)
Age 30to44	0.00650
	(0.0206)
Age 45to64	0.0530**
	(0.0216)
Over 65	0.000460
	(0.0193)
Constant	-0.000131
	(0.0206)
Observations	134
R^2	0.544

Robust standard errors in parentheses
* p<.1, ** p<.05, *** p<0.01

Figure 9 presents the mean annual household probabilities of WSL participation associated with living in a specific school zone. In looking at Figure 1 the zones that have a high cumulative percentage of participants match up extremely well with the areas of high probability of participation in Figure 9.

Figure 10 illustrates the fixed-effects for each school zone. The fixed effects are in units of the annual probability of participation and have a mean of zero. As such, they represent the shared "neighborhood" anomaly in the probability of the WSL participation, relative to the average neighborhood. A positive value of 0.01 reflects that homes in a particular zone participate at a rate of 0.01 more on average than predicted by observable household characteristics alone. Figure 10 shows that an empirically significant portion of the variability in participation rates in Figure 9 is explained by the covariates in the first stage regression. However, there are still some "hot" and "cold" zones. Specifically, zones to the Northwest and Southeast participate at a higher rate than predicted by the first stage variables alone. These "hot" broadly coincide with zones of higher than normal participation in Figure 9. Interestingly, the more central zones are comparative "cold" spots.

Figure 10 shows these central "cold" spots cluster around the Vegas Strip. This area is the older part of Las Vegas, with the mean build year of the homes in these zones falling between the 1950s and 1970s. The city was built out from this central area, therefore the father out from this central area, the newer the neighborhoods tend to be. The majority of the "hot" zones, including the ones in the Northwest and Southeast were built after the mid-1990s. However, since house vintage was controlled for in the 1st

stage this leads me to believe there is some other unobserved characteristic driving this variability.

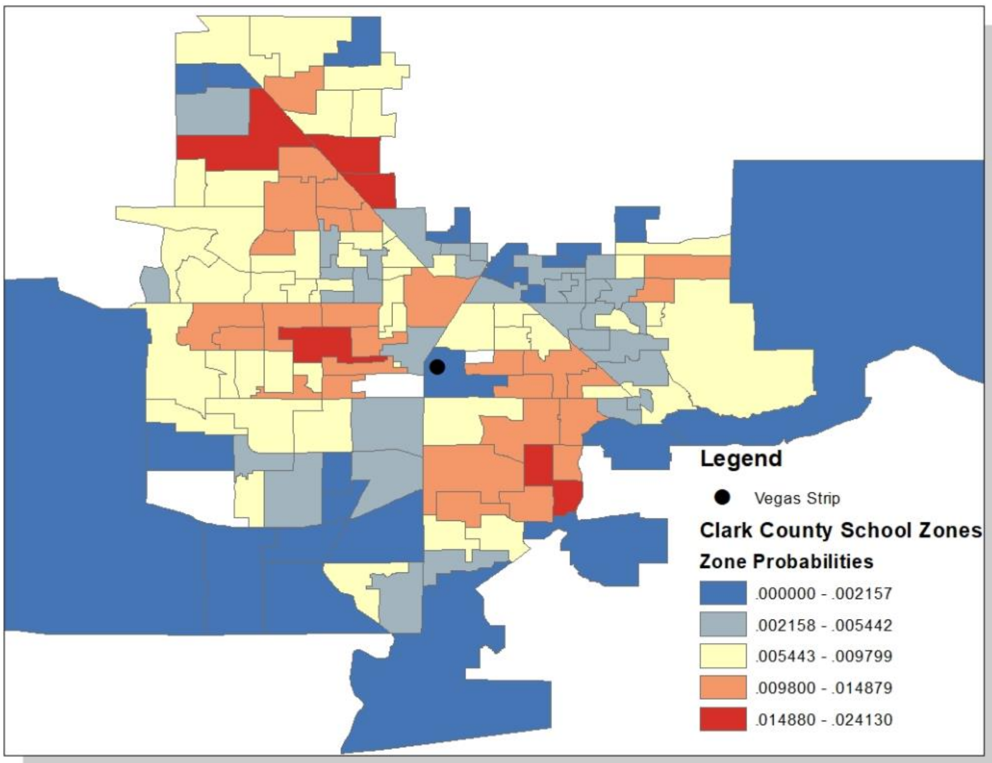

Figure 9 **Illustrates the average annual probability of household participation in each school enrollment zone**

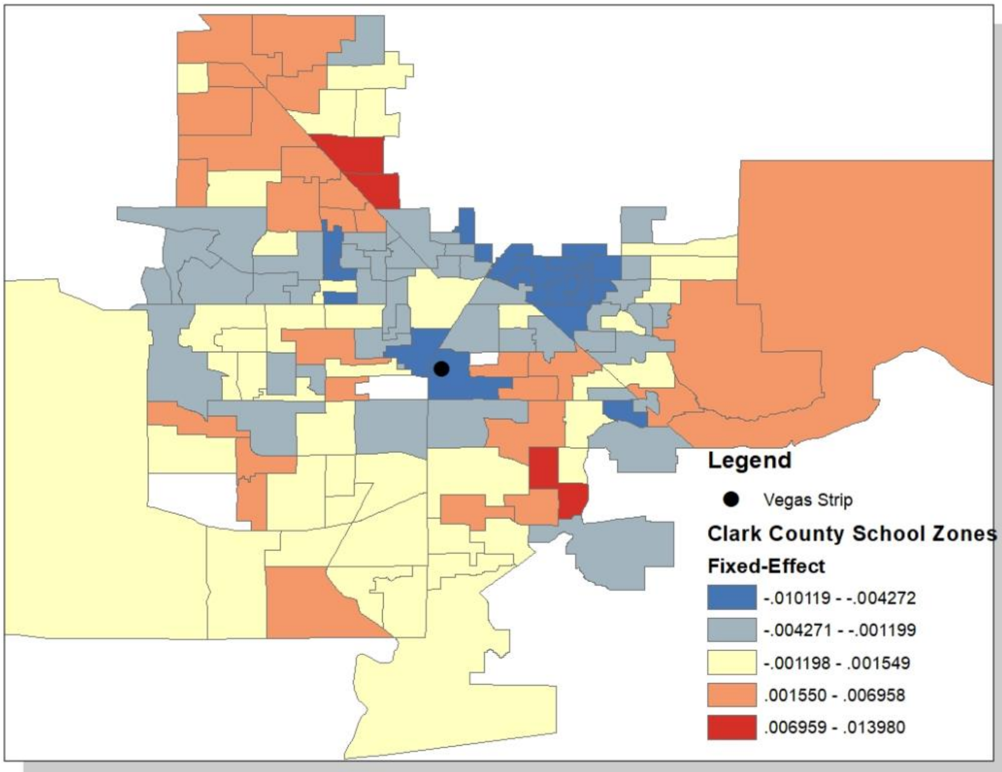

Figure 10 Displays the first-stage fixed-effects of each school zone.

In an attempt to explain this spatial variability I regressed the spatial fixed effects as a function of Census demographics. The complete results for the 2nd stage model can be found in Table 4. The coefficients in the second stage model are the effects of neighborhood-level demographics on the neighborhood anomaly in annual participation. Unlike the 1st stage models, here the majority of variables are not significant – perhaps due to the small number of observations. There are a few significant variables, however. Individuals in school zones with larger shares of households earning a salary between $100,000 and $150,000 are more likely to participate by 0.003 for every 10% increase. This effect may be attributed to the type of homes that attract people in this income bracket. Homes that could be afforded in this income range would most likely have a yard that could be converted. However, the income is perhaps not so high that incentives and water price wouldn't influence their decision to participate.

Areas that have high amount of large households (5 people or more) had a negative effect of 0.0039 on participation for a 1% increase. This makes sense since larger households most likely have children. Having a grass-covered area for children to play without leaving the property could be seen as more important that gains made from lawn conversion.

I also found that areas that had a high population of people between the ages of 45 and 64 had a positive effect on participation rates. This had the largest positive effect with a 1% increase resulting in a 0.0053 increase. This could be due to people within this age range being better suited to invest in their homes. Individuals younger than this are likely to have young children and other financial commitments (i.e. student loans) that take precedence over lawn conversion. Once an individual is older than 65 they be retired or nearing retirement and therefore less likely to make substantial home investments. Moreover, individual within this "middle-age" age range are less likely to have young children and are often at the peak of their lifetime earnings. Therefore, an investment like lawn conversion that would lower future water costs, would be appealing.

The other 2 variables that are found to be significant and have a negative effect are area with a larger Asian population and a larger share of residents with graduate degrees. The interpretation of these effects is not clear and may be driven by unobserved neighborhood variables correlated with these sociodemographic characteristics more than the characteristics themselves.

Conclusion:

The analysis of participation in the WSL program identifies key factors that influence a household's likelihood of enrollment. Here I find that larger yards, high water, the cost of water and specifically, the cost of outdoor water use are all influential in who chooses to participate. I also show how changes in rebate value, both increasing and decreasing, as well as water price are correlated with the characteristics of households that enroll. These are the primary drivers of participation found in the first stage of this study. While residency and parks yielded some interesting results, I would consider these as suggestive, but worthy of further investigation.

Though the results do not bring about strong connections between parks and residents' willingness or unwillingness to give up their lawns, there are more avenues that can and should be investigated. This study is limited to only analyzing homes in relation to distance to parks and park types, but not all green space are considered. Also, while this study looks at homes that converted from grass to xeric landscaping, there is no data that identified a homes landscape choice outside of the program. Adding these factors may shed some light on the effects of greenspace on participation.

In the 2nd stage I examine school zone "neighborhood" effects. Here I find there is significant evidence to show that neighborhood characteristics affect a household's probability of participation. Zones that have a high share of people between the age of 45 and 64, as well as those with a high middle income have a positive effect on participation. On the other side of the spectrum, school zones with a high amount of large households (over 5 people) have a negative effect. While these results do explain some of these neighborhood effects there is still more that needs to be known in order to complete the picture. Overall a more in-depth look at these effects and what the drivers are behind them needs to be taken in order to better understand how they influence participation.

One factor of note in this study is that the 2008 financial crisis was not controlled for since households were, to a varying extent, likely affected by the event. This made creating a control group to test the effects of the crisis on participation infeasible. It is also unclear what effect it had on participation. The crisis could have had a positive effect as it put pressure on households to save money, thereby increasing participation. This hypothesis is consistent with the significant increase in participation in 2008 shown in Figure 7. However, the spike in participation may also have been caused by the contemporaneous increase in the rebate. Nonetheless, the number of foreclosures that occurred would suggest that there were also homes with high probabilities of participation that did not enroll during this period due to bank ownership. Thus the overall effect of the crisis on participation is unknown.

While I have focused on the WSL program as a non-price program, the first-stage results do suggest how rebate programs can be used jointly with a price based approach to achieve higher levels of conservation through increased participation. The strong effects of summer marginal water prices and the difference between summer and winter water bills on participation suggest that changes in structure of water rates can significantly impact participation in the non-price program. Therefore price and non-price policies can be complementary; utilizing the changes in price in conjunction with a rebate can increase participation more than would be achievable with the rebate alone. Potential negative distributional effects of price increases on low-income households can be mitigated by careful design of block rates while also providing high marginal prices that are likely to primarily affect homes with large outdoor water use. Relatively low-income households with large amounts of water intensive landscaping can take advantage of generous rebates to replace their landscapes – providing transition mechanism for these households to avoid excessive water bills.

While here I look at the WSL program itself and how value changes of the rebate and the price of water affected participation, there is much room for further research. The SNWA created numerous programs during this time period and continues to do so. It would be worthwhile to extend the analysis to take into account the effect of interactions between these programs. Marketing, educational programs, and other information shocks could play a vital role in understanding why people chose to participate in the program. The availability of other rebate programs, such as the pool cover rebate, and the order in which they are initiated could also be important in understanding participation rates and the efficiency of the program.

In addition to expanding the effect of other policies on participation, a more in-depth look at the participants themselves and the role of social interactions in driving their water use is needed. Social characteristics have been found in numerous studies to be an important factor in whether someone chooses to voluntarily participate in a conservation program (Allcott, 2011; Attari 2014; Guerin et al., 2000; Lubell et al., 2017). People's social network and how they perceive themselves in comparison to their neighbors plays a role in decision-making. Social norms of an individual or a specific group of people can be a strong motivator in whether or not they participate in a program. The level of trust one has in the administrator of a program can also be a factor. This attribute would be particularly interesting, since the SNWA has a history of prioritizing transparency and building trust with the communities it works with.

As water scarcity becomes a more pressing issue in arid cities, devising more effective water management practices is imperative for achieving sustainability goals. Understanding the drivers of participation can help policymakers to craft more effective and targeted policies that satisfy water conservation targets in a cost-effective manner. It can also show how multiple policies – including combinations of water pricing and non-price policies – can be combined to augment participation, improve the selectivity, and mitigate undesirable distributional outcomes of individual programs. This knowledge can help water managers sustain their water supplies in an era of increasing scarcity.

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